Interactive Visualization of Factors Influencing Burnout Among Physicians (2014-2023)

GPH-M-3: Digital Health (WS24)

Submitted to: Prof. Dominik Böhler

Deggendorf Institute of Technology

Faculty European Campus Rottal-Inn

Master of Global Public Health, 4th Semester

Prepared by: Dr. Kaleb Abey Hailu, MD

Matriculation number: 22205716

Robert-Erbertseder-Weg 2, 84347 Pfarrkirchen. Germany.

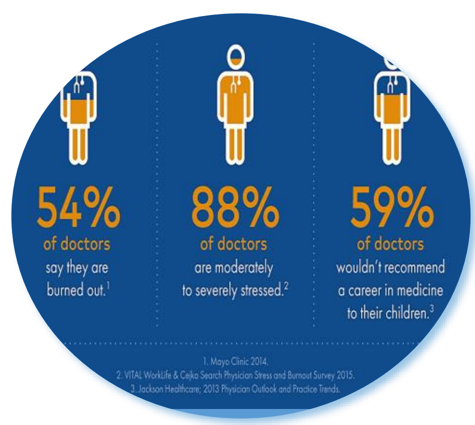
Pfarrkirchen, 12.07.2024

1. Introduction to Burnout

Burnout is a significant public health issue characterized by chronic workplace stress, leading to emotional exhaustion, depersonalization, and reduced personal accomplishment. It affects numerous professions globally, with severe consequences for health and productivity. In the United States, burnout-related healthcare spending ranges from $125 to $190 billion annually, while in Germany, burnout costs the economy approximately €9 billion each year. According to the APA's 2021 Work and Well-being Survey, 79% of employees experienced work-related stress in the month before the survey. Nearly 3 in 5 employees reported negative impacts, including lack of interest, motivation, or energy (26%) and lack of effort at work (19%). Additionally, 36% reported cognitive weariness, 32% reported emotional exhaustion, and 44% reported physical fatigue, marking a 38% increase since 2019.

Burnout leads to severe physical and psychological consequences, including obesity, type 2 diabetes, cardiovascular diseases, musculoskeletal pain, insomnia, depressive symptoms, and psychological ill-health symptoms. Employees who frequently experience burnout are 63% more likely to take sick days, 23% more likely to visit the emergency room, and 2.6 times more likely to leave their current employer. They are also 13% less confident in their performance.

Why Healthcare-workers



DeChant, Paul F. et al. (2019). Effect of Organization-Directed Workplace Interventions on Physician Burnout: A Systematic Review. Mayo Clinic Proceedings: Innovations, Quality & Outcomes, Volume 3, Issue 4, 384 - 408.

1.1. Leveraging Data Insights: Addressing Stakeholder Challenges and Uncovering Solutions for Burnout

Stakeholders	Challenges Resulting from Burnout	Impact of Data Visualization and Analysis
Government	Economic burden due to decreased productivity, increased healthcare spending, and social welfare costs. Burnout-related healthcare with physician turnover costs about $4.6 billion.	Efficient resource allocation by highlighting critical areas, facilitating policy development, and supporting evidence-based public health interventions.
Healthcare Sector	Increased demand for mental health services, higher prevalence of related diseases, extended patient wait times, and higher workload. Burnout among healthcare workers results in loss of skilled labor.	Identifies burnout hotspots for better workforce management and develops targeted interventions to improve staff well-being and patient care quality.
Industrial Sector	Reduced productivity, financial losses from absenteeism and sick days, and skilled labor shortages. Burnout significantly impacts overall industrial performance.	Provides insights into employee well-being and productivity trends, identifies high-risk roles for targeted wellness initiatives, and optimizes resource allocation and financial forecasting.
Education Sector	Burnout leads to poor academic performance, increased dropout rates, and reduced educational attainment, with significant implications for future professional lives.	Identifies at-risk student populations for tailored support, improves academic interventions, and enhances engagement through data-driven educational strategies.
Social Welfare	Increased demand, financial strain, and reduced access to benefits due to high burnout levels, leading to disparities in care quality.	Enables effective allocation of resources, enhances program effectiveness by identifying key areas of intervention, and reduces disparities through targeted support informed by comprehensive data.
General Public	Reduced quality of life, loss of income, higher healthcare costs, emotional and psychological burdens, and stigma associated with mental health issues.	Empowers individuals through awareness and education, improves access to mental health resources with clear data, and reduces stigma through public awareness campaigns and transparent data sharing.
Health Insurance Companies	Struggle to evaluate health metrics and wellness programs. Real-time data visualization aids in risk assessment and cost management, optimizing insurance plans.	Real-time data visualization for better risk assessment and evidence-based evaluation of wellness programs.
Healthcare	Limited time and resources for data	Enables rapid identification of patient

Professionals (HCPs)	collection and analysis, hindering the assessment of care quality and intervention effectiveness.	trends, facilitates collaboration through shared insights, and improves patient outcomes through data-driven care strategies.
Researchers and Scientists	Limited access to diverse datasets and ethical hurdles impede scientific progress.	Aggregated data for comprehensive research and trend analysis, enhancing understanding and practical application through detailed data visualization.
Public Health Surveillance Teams	Limited funding, fragmented data, and challenges in engaging the public without compelling data.	Effective surveillance and trend mapping prioritizes intervention areas through clear visual insights, and enhances public engagement through impactful data presentation.
Health Policy Makers	Challenges in implementing preventive healthcare policies without robust evidence and stakeholder support.	Provides compelling evidence for policy development and supports proactive healthcare measures through visualized positive outcomes.
Pharmaceutical Companies	Pharmaceutical Companies Difficulty obtaining relevant data for drug development and approval. Data-driven insights improve medication planning and production, addressing medication needs effectively through comprehensive data analysis.	Data-driven insights improve medication planning and production, addressing medication needs effectively through comprehensive data analysis.
Corporate Wellness and Fitness	Lack of objective health assessments and low engagement in wellness programs, leading to increased absenteeism and productivity losses.	Data visualization enhances engagement strategies, identifies specific vulnerabilities for targeted interventions, and improves productivity through effective wellness programs.
Educational Institutions	Limited resources to teach preventive healthcare and demonstrate its impact.	Enhances educational strategies through visualized health trends, improving student understanding and engagement in wellness initiatives.
Technology Developers	Challenges in creating relevant health technologies without medical and scientific expertise.	Access to large datasets and data-driven design improves the development of user-friendly health applications.

2. Steps to Address Burnout with Data Visualization / Solution: your pathway to finding a solution to the problem

2.1. Comprehensive Research and Data Collection

Effective solutions start with thorough research. Using databases like ResearchGate, Google Scholar, and PubMed, key terms such as “burnout,” “occupational stress,” and “workplace health” help gather relevant studies. Research shows that 76% of US employees experience burnout sometimes or often, and 29% of employees in Germany report feeling burnt out. Additionally, the APA’s 2021 Work and Well-being Survey found that 79% of employees had experienced work-related stress in the month before the survey.

2.2. Data Analysis and Assessment

Detailed analysis helps identify patterns and trends in burnout across professions and demographics. For instance, healthcare professionals globally report high burnout rates, with 72% experiencing burnout symptoms. In the US, physician turnover due to burnout costs about $4.6 billion annually.

2.3. Data Visualization Tools:

Scatter Plots: Evaluate the relationship between burnout levels and factors such as age, gender, and years in the profession. For example, a negative correlation between work-life balance and burnout can guide policy changes.

Graphs and Charts: Visualize trends, compare burnout rates across demographics, and assess intervention impacts. Bar charts, for example, can show burnout reduction after implementing resilience training.

Heatmaps: Identify burnout hotspots in different regions and professions.

Trend Lines: Track changes in burnout rates over time and predict future trends.

Correlation Matrices: Analyze relationships between burnout and factors like workload, work-life balance, and job satisfaction.

2.4. Identifying Key Stakeholders

Addressing burnout involves multiple stakeholders: governments, healthcare sectors, industrial sectors, education sectors, social welfare organizations, the general public, health insurance companies, researchers, public health surveillance teams, health policymakers, pharmaceutical companies, corporate wellness programs, educational institutions, and technology developers. Each plays a crucial role in mitigating burnout by contributing to research, policy development, resource allocation, and support systems. Governments face economic strain from decreased productivity and increased healthcare costs, while healthcare sectors struggle with increased demand for services and loss of skilled labor. Industrial sectors suffer from reduced productivity and financial losses, and education sectors deal with decreased academic performance and higher dropout rates. Social welfare organizations face increased demand and financial pressure, and the general public experiences reduced quality of life and higher healthcare expenses. Health insurance companies, researchers, public health surveillance teams, health policymakers, pharmaceutical companies, corporate wellness programs, educational institutions, and technology developers also play significant roles in addressing burnout.

2.5. Developing and Implementing Solutions with Data Visualization

A multifaceted approach using data visualization includes:

- **Systemic Changes**

Workload Management: Implement flexible scheduling and adequate staffing. Data dashboards track real-time workloads for adjustments.

Role Clarification: Ensure a clear understanding of roles to reduce stress. Visualization tools create organizational charts and role descriptions.

Mental Health Support: Provide accessible mental health resources. Data analytics monitor program uptake and effectiveness.

Supportive Organizational Climate: Foster a positive work culture. Visualization tracks employee satisfaction and engagement.

- **Preventive Measures**

Resilience Training: Enhance coping skills and promote resilience. Interactive dashboards monitor participation and progress.

Mindfulness Programs: Implement stress reduction techniques. Visualization tools track participation and outcomes.

- **Collaborative Efforts**

Public-Private Partnerships: Encourage cooperation for comprehensive programs. Data sharing platforms facilitate collaboration.

Community Involvement: Engage groups in promoting mental health. Community health maps track initiatives and impact.

- Data-Driven Interventions

Interactive Dashboards: Allow exploration of data on burnout rates and intervention outcomes.

Predictive Analytics: Use machine learning to predict at-risk employees and intervene proactively.

Geospatial Analysis: Map burnout rates to identify high-need areas.

- Policy Development

Legislation: Enact laws protecting mental health, using data to show policy impact.

Incentives for Employers: Provide financial incentives for effective burnout prevention programs. Visualization shows a return on investment.

- Education and Awareness

Training Programs: Offer manager and employee training on burnout. E-learning platforms track progress.

Public Awareness Campaigns: Use media to educate about burnout. Visual storytelling makes data accessible and engaging.

- Technological Solutions

Mental Health Apps: Develop apps providing resources and tracking stress levels. Visualized data monitors trends and personalizes interventions.

Telehealth Services: Offer virtual counseling and support, using data to optimize services.

3. Implementation: description of the detailed steps and settings in the tools used to show how the interactions and data generation are being built, specifically

I began by conducting background research on burnout, focusing on its definition, diagnostic criteria, and risk factors, as well as the types of plots suitable for visualizing these factors. I found that the Maslach Burnout Inventory (MBI) is the most widely used diagnostic tool for measuring burnout. For my study, even though finding a suitable dataset from Kaggle would have been easier I went through the long road of generating my data and then manipulating the data! I established a burnout score range of 1-10, with 1 indicating the lowest level and 10 the highest, setting a score of 7 or above as the threshold for Diagnosis of burnout.

I selected various risk factors based on their established relevance in previous studies: Year, Age, Gender, Marital Status, Profession, Years in Profession, Work-Life Balance, and Job Satisfaction. These factors have been consistently shown to correlate with burnout levels.

To generate the dataset, I initially used ChatGPT to produce a large list of results for each column, tailored to different professions. However, due to the limitations of the free version of ChatGPT, I obtained 2000 entries distributed evenly across ten years (2014-2023).

Subsequently, I used Python to refine the dataset, as the initial data provided by ChatGPT did not meet my expectations. I edited the dataset to better align with my envisioned structure and saved the final version as an XLSX file. The Jupyter notebook file detailing the initial processing and subsequent modifications is attached.

3.1. Code description for Cleaning the data set

```
# Load necessary libraries

library(dplyr)

library(readr)



# Load the dataset

burnout_data <- readr::read_csv("Burnout_Modified2.csv")


# Clean the dataset and rename columns

cleaned_data <- burnout_data %>%

  # Remove rows with missing values

  tidyr::drop_na() %>%

  # Remove duplicate rows

  distinct() %>%

  # Correct any data inconsistencies if needed (example shown for Gender)

  mutate(Gender = recode(Gender, 'M' = 'Male', 'F' = 'Female')) %>%

  # Rename columns for consistency

  rename(
```

```
  patient_id = `Patient ID`,
  year = `Year`,
  age = `Age`,
  gender = `Gender`,
  marital_status = `Marital Status`,
  profession = `Profession`,
  years_in_profession = `Years in Profession`,
  work_life_balance = `Work-Life Balance`,
  job_satisfaction = `Job Satisfaction`,
  burnout_level = `Burnout Level`,
  burnout_category = `Burnout Category`
 )

# Save the cleaned dataset to a new CSV file
readr::write_csv(cleaned_data, "Cleaned_Burnout_Modified2.csv")

# Print the first few rows of the cleaned dataset
print(head(cleaned_data))
```

3.2. Code Description for Data Visualization Project

3.2.1. Loading Libraries:

Essential libraries are loaded for data manipulation (dplyr, tidyr), reading CSV files (readr), creating plots (ggplot2), making plots interactive (plotly), building Shiny apps (shiny, shinythemes), and tidying model outputs (broom).

```
# Load necessary libraries
library(dplyr)
library(tidyr)
```

```
library(readr)
library(ggplot2)
library(plotly)
library(shiny)
library(shinythemes)
library(broom)  # For tidying model outputs
```

3.2.2. Reading the Data: The cleaned dataset is read from a specified file path. This step is crucial as it loads the data needed for visualization.

```
cleaned_data <- readr::read_csv("Cleaned_Burnout_Modified2.csv")
```

3.2.3. Defining the UI:

Sets up the user interface of the Shiny app. Users can select variables for the X-axis, choose a year, and decide whether to show a regression line. The shiny::fluidPage() function structures the layout with a sidebar for inputs and a main panel for outputs.

UI Elements:

- shinythemes::shinytheme("cerulean"): Applies a theme to the app.
- shiny::selectInput(): Dropdowns for selecting X-axis variable and year.
- shiny::checkboxInput(): Checkbox for showing a regression line.
- shiny::tabsetPanel(): Tabs for "Home" and "Plot" sections.

```
# Define UI for the app
ui <- shiny::fluidPage(
  theme = shinythemes::shinytheme("cerulean"),
  shiny::titlePanel("Burnout Levels Visualization"),
  shiny::sidebarLayout(
    shiny::sidebarPanel(
      shiny::selectInput("xaxis", "Select X-axis Variable:",
                  choices = c("age", "gender", "marital_status", "years_in_profession", "work_life_balance",
"job_satisfaction")),
```

```
    shiny::selectInput("year", "Select Year:",
                    choices = c("2014", "2015", "2016", "2017", "2018", "2019", "2020", "2021", "2022",
"2023", "All")),
    shiny::checkboxInput("regression", "Show Regression Line", value = FALSE),
    width = 3
  ),
  shiny::mainPanel(
    shiny::tabsetPanel(
      shiny::tabPanel("Home",
                  shiny::h3("Burnout Levels Visualization Dashboard"),
                  shiny::p("This dashboard provides insights into burnout levels across various medical
professions based on different factors such as age, gender, marital status, years in the profession, work-
life balance, and job satisfaction."),
                  shiny::p("Key insights include identifying the highest and lowest burnout levels among
professions, understanding the impact of demographic factors on burnout, and exploring the correlation
between work-life balance or job satisfaction with burnout levels."),
                  shiny::p("Use the sidebar to select different variables and years to visualize the data. Toggle
the regression line option to see the trend between variables.")
      ),

      shiny::tabPanel("Introduction",
                  shiny::h3("Brief introduction to the burden of Burnout"),
                  shiny::p("Burnout is a significant public health issue characterized by chronic workplace
stress, leading to emotional exhaustion, depersonalization, and reduced personal accomplishment. It
affects numerous professions globally, with severe consequences for health and productivity. In the
United States, burnout-related healthcare spending ranges from $125 to $190 billion annually, while in
Germany, burnout costs the economy approximately €9 billion each year. According to the APA's 2021
Work and Well-being Survey, 79% of employees experienced work-related stress in the month before the
survey. Nearly 3 in 5 employees reported negative impacts, including lack of interest, motivation, or
energy (26%) and lack of effort at work (19%). Additionally, 36% reported cognitive weariness, 32%
reported emotional exhaustion, and 44% reported physical fatigue, marking a 38% increase since
2019."),
                  shiny::p("Burnout leads to severe physical and psychological consequences, including
obesity, type 2 diabetes, cardiovascular diseases, musculoskeletal pain, insomnia, depressive symptoms,
and psychological ill-health symptoms. Employees who frequently experience burnout are 63% more
```

```
likely to take sick days, 23% more likely to visit the emergency room, and 2.6 times more likely to leave their current employer. They are also 13% less confident in their performance."),
    ),
    shiny::tabPanel("Plot",
            plotly::plotlyOutput("plot"),
            shiny::textOutput("description")
    )
   )
  )
 )
)
```

3.2.4 Filtering Data: A reactive function filters the data based on the selected year. If "All" is selected, the entire dataset is used; otherwise, the data is filtered to the chosen year.

```
# Define server logic
server <- function(input, output) {
 filtered_data <- shiny::reactive({
  if(input$year == "All") {
   data <- cleaned_data
  } else {
   data <- dplyr::filter(cleaned_data, year == as.numeric(input$year))
  }
  data
 })
```

3.2.5. Rendering Plots:

This section handles the generation of plots.

- **Data Grouping and Summarization**: Groups data by profession and calculates average values for the selected variable and burnout levels.
- **Scatter Plot**: Creates a scatter plot for variables like work-life balance and job satisfaction.

- **Customization**: Labels axes and title, applies a theme, and sets y-axis limits.

```
#Rendering Plots
 output$plot <- plotly::renderPlotly({
   data <- filtered_data()
   x_var <- input$xaxis

   if(x_var %in% c("work_life_balance", "job_satisfaction")) {
     plot_data <- data %>% dplyr::group_by(profession) %>%
       dplyr::summarize(avg_value = mean(!!rlang::sym(x_var), na.rm = TRUE),
                        burnout_level_avg = mean(burnout_level, na.rm = TRUE),
                        count = n(), .groups = 'drop')

     p <- ggplot2::ggplot(plot_data, ggplot2::aes(x = avg_value, y = burnout_level_avg, size = count, color
= profession)) +
       ggplot2::geom_point(alpha = 0.7) +
       ggplot2::labs(x = paste("Average", gsub("_", " ", x_var)), y = "Average Burnout Level (0-10)", title =
"Burnout Level by Profession") +
       ggplot2::theme_minimal() +
       ggplot2::scale_y_continuous(limits = c(0, 10))
```

3.2.6. Adding Regression Line: If the regression line checkbox is selected:

- **Model Creation**: Builds a linear model.
- **R-squared calculation**: Determines the strength of the correlation.
- **Plot Adjustment**: Adds a regression line and annotation indicating the R-squared value and correlation interpretation.

```
#Adding regression line
     if (input$regression) {
       lm_model <- lm(burnout_level_avg ~ avg_value, data = plot_data)
```

```
r_squared <- summary(lm_model)$r.squared

interpretation <- ifelse(r_squared >= 0.5, "strong", "weak")

p <- p + ggplot2::geom_smooth(method = "lm", se = FALSE, color = "red") +

  ggplot2::annotate("text", x = Inf, y = Inf, label = paste("R-squared:", round(r_squared, 2), "-",
interpretation, "correlation"),

          hjust = 1.1, vjust = 2, size = 4, color = "blue")

}
```

3.2.7. Bar Plots for Age: If age is selected:

- **Age Grouping**: Groups data into age brackets.
- **Summarization**: Calculates average burnout levels for each age group and profession.
- **Bar Plot Creation**: Visualizes burnout levels by age group and profession.

```
#Bad plots for age

 } else {

   if (x_var == "age") {

    plot_data <- data %>% dplyr::mutate(age_group = cut(age, breaks = seq(20, 65, by = 5))) %>%

     dplyr::group_by(profession, age_group) %>%

     dplyr::summarize(burnout_level_avg = mean(burnout_level, na.rm = TRUE), count = n(), .groups =
'drop')


    p <- ggplot2::ggplot(plot_data, ggplot2::aes(x = age_group, y = burnout_level_avg, fill = profession))
+

     ggplot2::geom_bar(stat = "identity", position = "dodge") +

     ggplot2::labs(x = "Age Group", y = "Average Burnout Level (0-10)", title = "Burnout Level by Age
Group and Profession") +

     ggplot2::theme_minimal() +

     ggplot2::scale_y_continuous(limits = c(0, 10))
```

3.2.8. Bar Plots for Gender: If gender is selected:

- **Grouping and Summarization**: Group data by profession and gender, Making sure that all the variables in the x-axis in this case profession are written vertically to make sure that there is enough space.

```
} else if (x_var == "gender") {
  plot_data <- data %>% dplyr::group_by(profession, gender) %>%
    dplyr::summarize(burnout_level_avg = mean(burnout_level, na.rm = TRUE), count = n(), .groups = 'drop')

  p <- ggplot2::ggplot(plot_data, ggplot2::aes(x = profession, y = burnout_level_avg, fill = gender)) +
    ggplot2::geom_bar(stat = "identity", position = "dodge") +
    ggplot2::labs(x = "Profession", y = "Average Burnout Level (0-10)", title = "Burnout Level by Gender and Profession") +
    ggplot2::theme_minimal() +
    ggplot2::scale_y_continuous(limits = c(0, 10)) +
    ggplot2::theme(axis.text.x = ggplot2::element_text(angle = 90, vjust = 0.5, hjust = 1))
```

3.2.9. Bar Plots for Other Variables: This section handles the creation of bar plots for other selected variables like marital status, and years in profession.

- **Marital Status**: Groups data by profession and marital status, then creates bar plots to visualize burnout levels.
- **Years in Profession**: Groups data by profession and years in profession, then creates bar plots to visualize burnout levels.

```
} else if (x_var == "marital_status") {
  plot_data <- data %>% dplyr::group_by(profession, marital_status) %>%
    dplyr::summarize(burnout_level_avg = mean(burnout_level, na.rm = TRUE), count = n(), .groups = 'drop')

  p <- ggplot2::ggplot(plot_data, ggplot2::aes(x = profession, y = burnout_level_avg, fill = marital_status)) +
    ggplot2::geom_bar(stat = "identity", position = "dodge") +
```

```
ggplot2::labs(x = "Profession", y = "Average Burnout Level (0-10)", title = "Burnout Level by Marital Status and Profession") +

ggplot2::theme_minimal() +

ggplot2::scale_y_continuous(limits = c(0, 10)) +

ggplot2::theme(axis.text.x = ggplot2::element_text(angle = 90, vjust = 0.5, hjust = 1))

} else if (x_var == "years_in_profession") {

plot_data <- data %>% dplyr::mutate(years_group = cut(years_in_profession, breaks = seq(0, max(data$years_in_profession, na.rm = TRUE), by = 5))) %>%

dplyr::group_by(profession, years_group) %>%

dplyr::summarize(burnout_level_avg = mean(burnout_level, na.rm = TRUE), count = n(), .groups = 'drop')
```

3.2.11. Rendering Interactive Plots: The plotly::ggplotly(p) function is used to convert ggplot objects into interactive plots, enhancing user interaction and exploration capabilities.

```
p <- ggplot2::ggplot(plot_data, ggplot2::aes(x = years_group, y = burnout_level_avg, fill = profession)) +

ggplot2::geom_bar(stat = "identity", position = "dodge") +

ggplot2::labs(x = "Years in Profession", y = "Average Burnout Level (0-10)", title = "Burnout Level by Years in Profession and Profession") +

ggplot2::theme_minimal() +

ggplot2::scale_y_continuous(limits = c(0, 10))

}

}

plotly::ggplotly(p) %>% plotly::config(displayModeBar = TRUE)

})

# Adding text description based on the selected x-axis variable

output$description <- shiny::renderText({

x_var <- input$xaxis
```

description <- switch(x_var,

"age" = "This visualization shows the burnout levels across different age groups and professions. Key observations include:

- The highest burnout in Neurology for the age group 30-35.

- Burnout levels are generally high across all age groups, with notable peaks in specific professions.

- Younger to middle-aged physicians (30-40) tend to report higher burnout, particularly in high-stress specialties like Neurology and Emergency Medicine.

- This data suggests a need for targeted interventions to manage burnout, especially among younger physicians in high-stress fields.",

"gender" = "This bar chart compares the average burnout levels among various medical professions, segmented by gender. Key observations include:

- Highest burnout levels in Obstetrics/Gynecology for both genders, with females showing higher burnout levels.

- Lower burnout levels in Opthalmology and Radiology , particularly for males. There is least gender gap in ENT and Dermatology.

- Noticeable differences in certain fields like Dermatology, General Surgery, and Orthopedic Surgery, which show significant gender differences in burnout levels.",

"marital_status" = "This chart illustrates the relationship between marital status and burnout levels across different professions. Key observations include:

- Higher burnout in Emergency Medicine and General Surgery.

- Pathology and Ophthalmology have the lowest burnout levels.

- Single physicians generally report higher burnout levels compared to their divorced and married counterparts.

- Divorced physicians also show higher burnout levels but less than single physicians.

- Married physicians have the lowest burnout levels across most professions.

- Interpretation: Single physicians experience the highest burnout, indicating a potential lack of personal support. Emergency Medicine and Surgery are particularly high-stress fields, exacerbating burnout regardless of marital status.",

"years_in_profession" = "This chart illustrates the relationship between years in profession and burnout levels across different medical professions. Key observations include:

- Generally higher burnout levels in the initial years (0-5) across most professions.

- Mid to late career trends show varied burnout levels among professions, with some showing a decrease and others remaining high or increasing slightly.

- Emergency Medicine and Obstetrics/Gynecology consistently show higher burnout levels across all experience ranges.",

"work_life_balance" = "This scatter plot shows the correlation between average work-life balance and average burnout levels across various professions. Key observations include:

- A clear negative correlation, indicating that higher work-life balance is associated with lower burnout levels.

- High burnout and low work-life balance in professions such as Emergency Medicine, Obstetrics/Gynecology, and Family Medicine.

- Lower burnout and higher work-life balance in professions like Radiology and Pathology.",

"job_satisfaction" = "This scatter plot shows the correlation between job satisfaction and burnout levels across various professions. Key observations include:

- A negative correlation, indicating that higher job satisfaction is associated with lower burnout levels.

- High burnout levels in professions such as Emergency Medicine and Anesthesiology, which also have lower job satisfaction.

- Lower burnout levels in professions like Dermatology and ENT, which also have higher job satisfaction."

```
    )
    description
  })
}
```

3.2.12. Running the program!

```
# Run the application
shiny::shinyApp(ui = ui, server = server)
```

The long-suffering that comes with trying to publish on Shiny while using a local Directory(path) is a mistake I dare never repeat again!, it took me days to figure it out! Lesson learned!

Initial data visualization to make sure I have the right set of data was done in Python and can be accessed both in my GitHub https://github.com/Caleblak/Digital-Health-R-studio-final-project.git.

These references were initially used to assess and understand the general outlook of Burnout.

References

Awa, W. L., Plaumann, M., & Walter, U. (2010). Burnout prevention: A review of intervention programs. Patient Education and Counseling, 78(2), 184–190. https://doi.org/10.1016/j.pec.2009.04.008

Bretland RJ, Thorsteinsson EB. Reducing workplace burnout: the relative benefits of cardiovascular and resistance exercise. PeerJ. 2015 Apr 9;3

. doi: 10.7717/peerj.891. PMID: 25870778; PMCID: PMC4393815.

DeChant, Paul F. et al. (2019). Effect of Organization-Directed Workplace Interventions on Physician Burnout: A Systematic Review. Mayo Clinic Proceedings: Innovations, Quality & Outcomes, Volume 3, Issue 4, 384 - 408.

Greenglass, E. R. (1991). Burnout and gender: Theoretical and organizational implications. Canadian Psychology / Psychologie canadienne, 32(4), 562–574. https://doi.org/10.1037/h0079042

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., ... & Goh, J. (2019). Estimating the attributable cost of physician burnout in the United States. Annals of internal medicine, 170(11), 784-790

Joyce S, Shand F, Tighe J, Laurent SJ, Bryant RA, Harvey SB. Road to resilience: a systematic review and meta-analysis of resilience training programmes and interventions. BMJ Open. 2018 Jun 14;8(6)

. doi: 10.1136/bmjopen-2017-017858. PMID: 29903782; PMCID: PMC6009510.

Koontalay, A., Suksatan, W., Prabsangob, K., & Sadang, J. M. (2021). Healthcare Workers' Burdens During the COVID-19 Pandemic: A Qualitative Systematic Review. Journal of multidisciplinary healthcare, 14, 3015–3025. https://doi.org/10.2147/JMDH.S330041

Korczak D, Huber B, Kister C. Differential diagnostic of the burnout syndrome. GMS Health Technol Assess. 2010 Jul 5;6

. doi: 10.3205/hta000087. PMID: 21289882; PMCID: PMC3010892.

Koutsimani, P., Montgomery, A., & Georganta, K. (2019). The Relationship Between Burnout, Depression, and Anxiety: A Systematic Review and Meta-Analysis. Frontiers in psychology, 10, 284. https://doi.org/10.3389/fpsyg.2019.00284

Lluch, C., Galiana, L., Doménech, P., & Sansó, N. (2022). The Impact of the COVID-19 Pandemic on Burnout, Compassion Fatigue, and Compassion Satisfaction in Healthcare Personnel: A Systematic Review of the Literature Published during the First Year of the Pandemic. Healthcare, 10(2), 364. https://doi.org/10.3390/healthcare10020364

Rotenstein, L. S., Torre, M., Ramos, M. A., Rosales, R. C., Guille, C., Sen, S., & Mata, D. A. (2018). Prevalence of Burnout Among Physicians: A Systematic Review. JAMA, 320(11), 1131–1150. https://doi.org/10.1001/jama.2018.12777

Ruotsalainen, J. H., Verbeek, J. H., Mariné, A., & Serra, C. (2015). Preventing occupational stress in healthcare workers. Cochrane Database of Systematic Reviews, (4).

Shanafelt TD, Boone S, Tan L, Dyrbye LN, Sotile W, Satele D, West CP, Sloan J, Oreskovich MR. Burnout, and satisfaction with work-life balance among US physicians relative to the general US population. Arch Intern Med. 2012 Oct 8;172(18):1377-85. doi: 10.1001/archinternmed.2012.3199. PMID: 22911330.

Shoman, Y., El May, E., Marca, S., Wild, P., Bianchi, R., Bugge, M., Caglayan, C., Cheptea, D., Gnesi, M., Godderis, L., Kiran, S., McElvenny, D., Mediouni, Z., Mehlum, I., Mijakoski, D., Minov, J., van der Molen, H., Nena, E., Otelea, M., & Guseva Canu, I. (2021). Predictors of Occupational Burnout: A Systematic Review.

Taranu, S. M., Ilie, A. C., Turcu, A.-M., Stefaniu, R., Sandu, I. A., Pislaru, A. I., Alexa, I. D., Sandu, C. A., Rotaru, T.-S., & Alexa-Stratulat, T. (2022). Factors Associated with Burnout in Healthcare Professionals. International Journal of Environmental Research and Public Health, 19(22), 14701. https://doi.org/10.3390/ijerph192214701

Ulfa, M., Azuma, M., & Steiner, A. (2022). Burnout status of healthcare workers in the world during the peak period of the COVID-19 pandemic. Frontiers in psychology, 13, 952783. https://doi.org/10.3389/fpsyg.2022.952783

Williams, V. C., Biswas, S., Rogers, J. R., & Sharma, S. V. (2017). Effect of a workplace wellness program on employee health and economic outcomes: A randomized clinical trial. Journal of Occupational Health Psychology, 22(4), 394–406.